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Original Article

ONLINE POWER SYSTEM CONTINGENCY SCREENING AND RANKING METHODS USING RADIAL BASIS NEURAL NETWORKS

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ABSTRACT

This paper presents a supervising learning approach using Multilayer Feed Forward Neural Network(MFFN) and Radial Basis Fuction Neural Network(RBFN) to deal with fast and accurate static security assessment (SSA) and contingency analysis of a large electric power systems. The degree of severity of contingencies is measured by two scalar performance indices (PIs): Voltage-reactive power performance index, PIVQ and line MVA performance index, PIMVA. For each (N-1) contingency, thePerformance Index (PI) is computed using the Newton Raphson (NR) method. A correlation coefficient feature selection technique has been utilized to identify the inputs for the MFFN and RBFN. The proposed method has been applied on an IEEE 39-bus New England test system at different operating conditions comparing to single line outage and the results demonstrate the suitability of the methodology for on-line power system security assessment at Energy Management Center. The performace of the proposed ANN models is compared withNewton Raphson (NR) method and the results shows that the proposed model is effective and reliable in terms of static security assessment of power systems.

KEYWORDS: PerformanceIndex, Static Security Assessment, Contingency Analysis, Supervised Learning, Multilayer Feed Forward Neural Network, Radial Basis function Network

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INTRODUCTION

Security assessment of a power systemplays an important role for on-line applicationsat Energy Management Centerwhich employs to examine the steady state performance of a power system after contingency. Nowdays, electric power system move towards a new environment that is deregulation which has forced modern electric utilities to operate their systems under highly stressed conditions closer to their security limits. Therefore, the system operators needs to develop quick and more precise ranking methods for analyzing the power system security violations and severity level of contingencies to keep the power system in safe operating limits. As indicated by the fast development of Machine Learning (ML) applications in power system area, this paper presents a review of Artificial Neural Network (ANN) in Static Security Assessment (SSA).

Many research papers have discussed different methods to simulate and rank the contingencies for instance, automatic contingency selection based on a pattern analysis as proposed by Rodrigues [Rodrigues, 1999]. This method is capable to identify the potential harmful contingencies.On the other hand, Dynamic security assessment (DSA) enables to determine which contingencies may cause power system operating limit violations or system instability.So far, the only Transient Energy Function (TEF) analytical methods are suggested for dynamic security assessment [2] and the use of Artificial Intelligence including Neural Networks and Expert Systems [3]. In [4] Transient stability assessment of power system using Probabilistic Neural Network (PNN) and Least Squares Support Vector Machine

(LS-SVM) was presented.For a given severity of contingencies any on-line TSA tool must provide a fast and accurate stability evaluation and system security analysis under random load perturbations.System security can be assessed using contingency analysis. Contingency analysis identified those cases which are harmful to the system and ranked them according to their severity is referred to as contingency selection.Ranking methods employs two scalar performance index (PI) to measure the severity of each single line outage [5-7].In [8] a cascade neural network-based approach is proposed for fast line flow contingency selection and ranking. The developed cascade neural network is a combination of a ranking module and a filter module. Generally PI-based methods are difficult for online applications because of high computational time needed.

Recently, artificial neural networks have shown a great promise for contingency screening and ranking due to their ability to accurate input-output mappings. To estimate the severity of contingencies a pattern recognition technique is proposed in [9-11].Over the past few years, several approaches have been proposed for static security assessmentusing artificial neural networks (ANN) [12]–[14]. In [15] author employs ANN for online contingency screening and ranking and found that ANN is effective in terms of accuracy and speed. In this paper,two four-layered Multilayer Feed Forward Neural Network(MFFN) and Radial Basis Function Neural Network(RBFN) are proposedwhich predict the degree of severity of contingencies.The study involves RBFN is more accurate and faster than MFFN as RBF networks reduce the computation time required for training. Further due to minimum training error, the optimal learning can be achieved by RBF networks. The proposed ANN models are trained with Resilient back propagation algorithm for input–output mapping [16].

SYSTEM PERFORMANCE INDEX FORMULATION

In this paper the Performance Index (PI) is defined in terms of both bus voltage violations and line overloads is used for security level classification and to rank contingencies in order of their severityfollowing a given list of contingencies. The severity of a line contingency is measured by two scalar performance indices (PI), namely the line MVA performance index (PIMWA) and voltage reactive power performance index (PIVQ).

Line MVA Performance Index (PIMVA)

Most of the literature on contingency ranking show that the PI ranking methods is greatly influenced by line flow performance of the system. Line MVA Performance Index (PIMVA) [11] is expressed by the following scalar PI:

$$PI_{MVA} = \sum_{l=1}^{N_l} \left(\frac{W_{Li}}{M}\right)\left[\frac{S_l^{post}}{S_l^{\max}}\right]^{2n} \tag{1}$$

Where S_l^{post} is the post-contingency MVA flow of line l, $S_l^{\max}$ the MVA rating of line l, N_l the number of lines in the system, W_{Li} the real non-negative weighting factor (=1). n is the integer exponent. In this paper the value of n is fixed as 4 for the IEEE 39-bus test system.

Voltage-Reactive Performance Index (PIVQ)

The severity of a contingency to out of line voltage limits and generator reactive powerviolations is given by:

$$PI_{VQ} = \sum_{i=1}^{N_B} \left(\frac{W_{Vi}}{M}\right) \left[\frac{\left|V_i - V_i^{sp}\right|}{\Delta V_i^{Lim}}\right]^M + \sum_{i=1}^{N_G} \left(\frac{W_{Gi}}{M}\right) \left[\frac{Q_i}{Q_i^{\max}}\right]^{2n} \tag{2}$$

Where ΔV_i^{Lim} = voltage deviation limit; V_i = post contingent voltage at the ith bus; V_i^{sp} = rated voltage magnitude corresponding to bus i; W_{Vi} is the weighing coefficient(=1); Q_i = reactive power at bus i; $Q_i^{\max}$ = upper limit for reactive power generation at bus i; NG the number of generating units, NB number of buses, n is the integer exponent where n=4; W_{Gi} = real non-negative weighting factor(=1). According to the PIs value, three different security states have been considered for the contingencies which are mentioned as; Secure state if PI < 0.2, Critical state if 0.2 < PI < 0.8, Insecure state if PI > 0.8.

SUPERVISED LEARNING APPROACH FOR ONLINE STATIC SECURITY ASSESSMENT

In this paper, Supervised learning approach is used which automatically learn to recognize complex patterns and make intelligent decisions based on input/output parameters. The proposed model is based on Supervised Machine learningapproach employsmultilayer layer feed forward neural network (MFFN) and Radial Basis Function Neural Network (RBFN) for online static security assessment andfast contingency screening and ranking of power systems. This paper uses Resilient Back Propagation Algorithm for training the neural network. It is an adaptive weight learning algorithm, which adapt the weight step based on the local gradient information.Due to its weight update properties the resilient back propagation algorithm converges much faster than the conventional back propagation algorithm.Two types of ANNs are used for online static security assessment and contingency analysis; MFFN and RBFN.

PROPOSED METHODOLOGY

Proposed ANN Methodology for Performance Indices

The proposed ANN model selected for on-line security assessment is a multilayer layer feed forward neural network (MFFN) and Radial Basis Function Neural Network (RBFN) trained with Resilient back propagation algorithm.To avoid misclassification, separate ranking is obtained for PIVQ and PIMVA using two MFFNs and RBFN as shown in the block diagram of the proposed model in Figure 1(a) and Figure 1(b). For each contingency, the performance indexes are calculated by off-line Newton Raphson method.

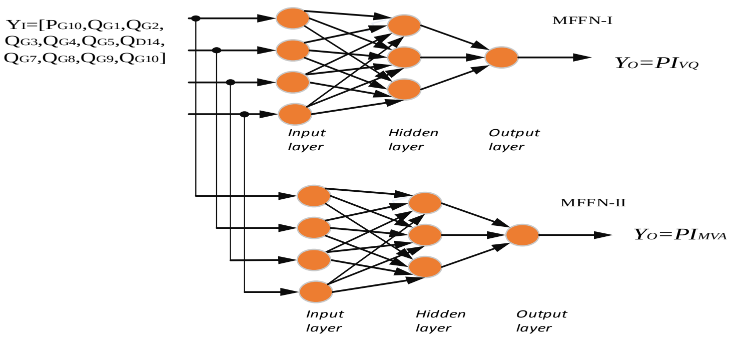

Figure 1(a): Proposed MFFNModel

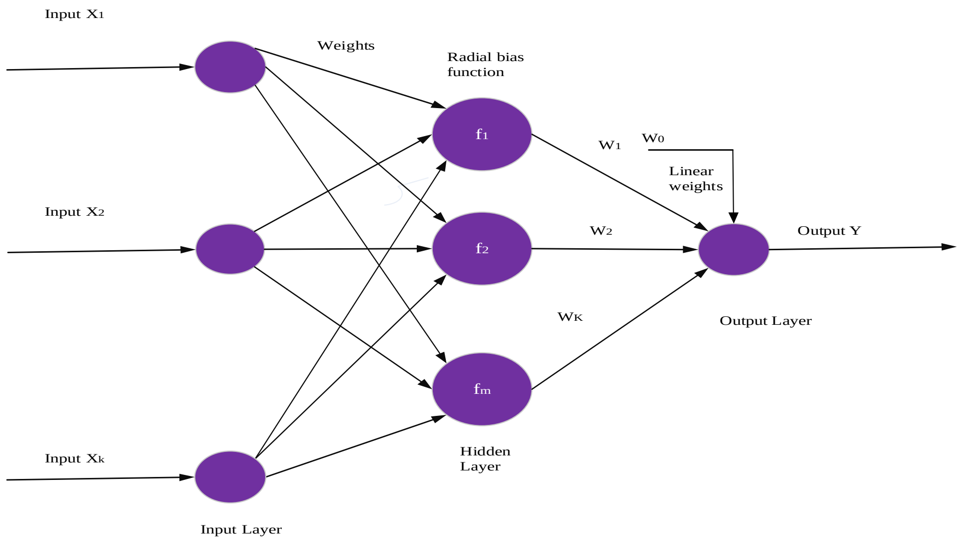

Figure 1(b): Proposed RBFN model

Multi-Layer Feed Forward Network (MFFN)

In this paper, MFFN consisting of three hidden layers with nonlinear activation functions is proposed for power system static security assessment. Real and reactive power generation at various generator buses and reactive power demand at load buses are chosen as the inputs to the MFFN. The activation function used in the hidden units is the "Tansig" and the output units, the linear function is used. The network is trained with "Resilient" back propagation algorithm [16] due to its good convergence properties. For two MFFNsand RBFN the parameters are shown in Table 1.

Radial Basis Function Neural Networks (RBFN)

The RBFN used in this paper is shown in Figure 1(b). The RBF network consists of single hidden layer feed forward structure. The input nodes pass the input variables directly to the hidden layer without any connection weights. The output of the *ith* hidden unit αi (X) is given by

$$\alpha_i(X) = \exp\left(-\frac{\left\| X - \mu_i \right\|^2}{2\sigma_i^2}\right) \tag{3}$$

WhereX is the input vector elements, μ_i is the vector which determines the center of the basis function α_i, σ_j is their widths. The k_{th}output node value $Y_k$is given as

$$Y_k(X) = \sum_{i=1}^{H} w_{ki}\,\phi_i(X) + w_{ko} \tag{4}$$

Where, w_{ki} = connection weight between the output and *i*hidden node w_{ko} = bias term and *p* is the number of the basis function. In this paper, RBFNgives faster convergence than the conventional MFFN.

Feature Selection

One of the key issues in ANN-based approach is the proper selection of inputs to the neural networks training. In this paper correlation coefficient technique has been used to select the appropriate training features for the MFNN and RBFN. The correlation coefficient between the jth and kth variable is calculated using (3) as

$$C_{jk} = \frac{E\{X_j X_k\} - E\{X_j\}E\{X_K\}}{\sigma_j \sigma_k} \quad \text{j, k = 1,2,3,4,…,n} \qquad (5)$$

The variables that are less correlated are selected as features for the MFNN and RBFN. In this paper pre-contingent real and reactive power generation at the generator buses (PG, QG), reactive power loads (QD) are selected as the input features for the proposed ANN training. Thus, 11 features (out of 62 features) are selected for the training of MFNN and RBFN.

Data Generation, Training, and Testing

In this paper, single line contingency is considered. The load patterns are generated by changing the loads randomly at each bus in the range of 80 and 143 % of their base case values. For each load pattern (N-1) contingency is simulated by Newton Raphson method. For each contingency, the Performance Index (PI) is calculated using (1) and (2). Nearly 11000 training patterns are generated for the proposed ANN model. The input features selected by correlation coefficient method is normalized in the range of 0.1 and 0.9 for each load pattern. Once the training of ANNs is accomplished, the trained network is evaluated by test data. The contingencies are ranked in terms of severity based on the performance index PI.

TEST SYSTEMS AND SIMULATION RESULTS

In this paper the simulation results of IEEE 39-bus New England system is discussed. The effectiveness of the proposed method showsthe suitability of the methodology for on-line power system security assessment at Energy Management Center. The test system consists of 10 generators, 12 transformers and 46 transmission lines [20]. The diagram of IEEE 39-bus New England system is shown in Figure 2.

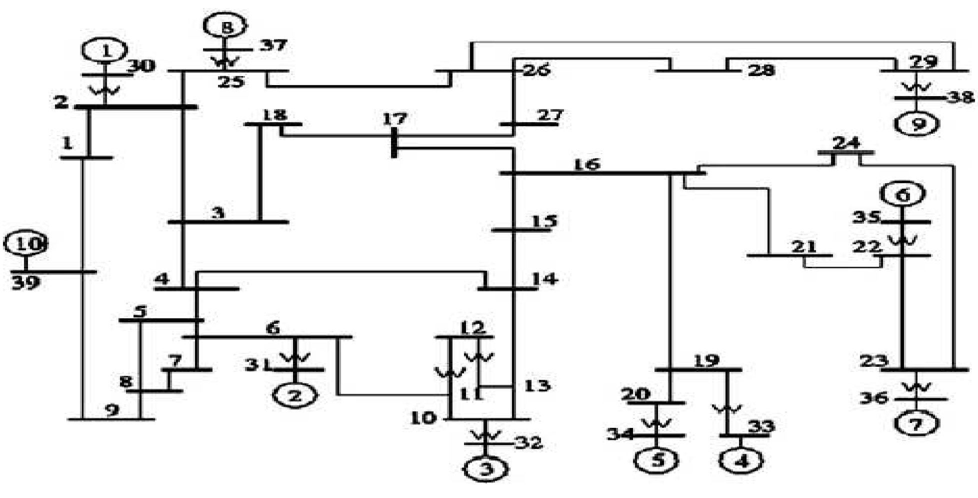

Figure 2: Single Line Diagram of IEEE 39-Bus New EnglandTest System

For contingency ranking bus no. 39 is taken as slack bus.The number of neurons in the hidden units is 30 and 10.

Table 1: Training Parameters

Parameter	MLFFN	RBFN
Maximum epochs	1000	-
Performance goal	0	-
Minimum gradient	1x e-10	-
Learning rate	0.05	-
Momentum coefficient	0.90	-
Gaussian function spread	-	0.1

Table 2: Sample Results of PI Calculations by MFNN and RBF

% Base Case	Line No.	Out Age No.	PIVQ			Class (PIVQ)		PIMVA			Class (PIMVA)	
			NR	MFNN-1	RBF	NR	MFNN-1	NR	MFNN-2	RBF	NR	MFNN-2
142.5	12-13	8069	0.9000	0.8856	0.8950	III	III	0.2296	0.2205	0.2270	II	II
100	4-14	6072	0.2255	0.2628	0.2210	II	II	0.1235	0.1225	0.1220	I	I
140	25-26	5206	0.3594	0.3031	0.3480	II	II	0.2056	0.2068	0.2040	II	II
105	6-7	6699	0.3080	0.2925	0.2993	II	II	0.1743	0.1721	0.1715	I	I
115	14-15	8028	0.1786	0.1878	0.1710	I	I	0.1301	0.1327	0.1298	I	I
120	23-24	9062	0.1896	0.1908	0.1808	I	I	0.1428	0.1389	0.1405	I	I
132.5	9-39	3141	0.5076	0.4806	0.4980	II	II	0.2143	0.2221	0.2118	II	II

Class I and Class II (critical); Class III (non-critical).

11,000 load patterns were generated by varying the loads randomly at all the buses and generation in the range of 80– 143% of their base case values. For 240 different loading conditions, 46 single line outages are simulated for each loading, to obtain different operating conditions. Contingency analysis has been performed by utilizing the pre-contingency data and the line performance indices for each load scenario and each outage at a time. A total of 8840 patterns have been taken to analyze the performance of the proposed model and for remaining cases Newton Raphson (NR) failed to converge. The test results of the proposed MFNN and RBF model for contingency screening and ranking is shown in Table 2. It is observed that PI values obtained by the proposed MFNN and RBF model are close to desired values of PI obtained from Newton Raphson method. It can be concluded from the table that for performance indices, PIVQ and PIMVA a separate ranking must be done. For sample result for 132.5 % of base case, it is found that operating constraints are violated for outage of line 9–39, resulting in system is insecure as both the PIs are in insecure classes. Such result is expected since bus No. 39 is a generator bus and line outage 9–39 causes bus voltage limit violation, the reactive power generation limit violation and the overloading of the transmission lines connected to bus No. 9. The outage of line 12–13 for both 142.5% of base case makes the system critical as again all the operational constraints are violated. Similar analysis can be drawn for other line outages. The number of cases that belong to the Class (I to III) obtained from the proposed MFNN and RBF model and their comparison with Newton Raphson method is shown in Table 2. Table 1 shows the parameters for the proposed MFNN and RBF model. The PI values obtained from MFNN and RBFneural network are very close with PI values obtained from Newton Raphson method.

CONCLUSIONS

In this paper power system static security assessment has been investigated. The test results presented on IEEE 39-bus system provides the following observations.

- A new method has been developed for calculating voltage performance and line performance index for contingency ranking which eliminates misranking and masking problems.
- The performace of the proposed models is compared with Newton Raphson (NR) method and the results shows that the RBF model is more effective and reliable in terms of static security assessment of power systems.
- Training is very fast as the RBF network has the capability of handling large amount of data.
- Testing time is less than 0.25sec.

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